LITERATURE REVIEW AND COMPETITOR ANALYSIS

MScFE Capstone Project

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Problem Statement

Conventional portfolio strategies, like Markowitz's Modern Portfolio Theory, have been around for quite a while. However, in real-world scenarios, they often fall short. This is mainly because they assume that asset correlations remain stable and that returns are always normally distributed.

This study presents a more flexible and dynamic approach to portfolio allocation by leveraging machine learning to overcome existing limitations. The main challenge lies in shifting from static optimization to a data-driven strategy that takes into account historical trends and market conditions. To evaluate how effectively four different machine learning models can optimize an asset portfolio, this research will develop, backtest, and compare them: LSTM, Random Forest, XGBoost, and Reinforcement Learning.

Literature Review

Introduction

The area of portfolio management is adapting to the shift from basic mean-variance optimization to multi-layered and complex data-driven and computational systems. The main cause of this shift is the acknowledgement that traditional portfolio strategies, while elegant, are often non-applicable to real-world situations. This is due to changes within markets and non-linear characteristics of assets. More financial data combined with higher computational power defends the argument that machine learning techniques are the most efficient and applicable modern tools to close the gaps in classical financial models (Olubusola, 2024). These approaches to portfolio optimization hold the most promise because they are flexible, and incorporate and adapt to changes in complex and fractal market structures. They do not optimize portfolios based on assumptions but on real-world market dynamics.

This literature review analyzes the foremost scholarly works that constitute the basis for this evolution, identifying contemporary research trends at the convergence of machine learning and finance and outlining particular gaps in the literature. It begins with a review of the critiques that have been articulated against the classical portfolio theories and the constraints they have, and continues with an examination of the different machine learning techniques, such as supervised learning, deep learning, and reinforcement learning, in the context of portfolio optimization. Finally, it reviews the literature from the perspective of comparative studies and articulates the research gap that this work aims to address. It specifically focuses on the lack of an empirical evaluation of a range of machine learning techniques within a single framework.

Limitations of Traditional Portfolio Theory

Markowitz's Modern Portfolio Theory, or MPT, forms the basis of modern portfolio management due to its mathematical description of how to build a portfolio of assets that achieves maximum expected return for a given risk (Leković, 2021). The investor only needs to plug in the expected returns, variances, and covariances of the assets.

Despite the influence and the theoretical elegance of MPT, it has considerable challenges in its practical application. One significant issue is the imputations, especially of the expected returns and the covariance matrix, to which the approach is very highly sensitive. Samartzis (2023) argues that MVO has been noted to function as an "error maximizer," meaning that small mistakes in estimating the inputs can cause large, illogical shifts in optimized portfolio weights. The assumption of stable, and hence correlating, returns as well as normally distributed returns in the approach has repeatedly been shown to be a problem. In financial markets, these correlations are time-variant (volatility clustering), are under- or over-distributed (fat tails), and do not correlate at all (time-varying correlations). The lack of dynamic adaptability in MVO is also a problem, as it has to be static to keep its applied logic (Odunaike, 2025). Ignoring the skewness in returns which is often present in financial markets leads to further complications in the practical application of MPT.

Literature has associated positive skewness with growth stocks more than value stocks, but the traditional MVO fails to recognize this higher-moment behavior. Moreover, the frameworks still put up barriers for investors trying to incorporate their expectations regarding future performance of the assets, this was somewhat addressed in later extensions like the Black-Litterman model. The conventional portfolio strategies mentioned above are the fundamental gaps that ML techniques attempt to fill. As the markets have become more intricate and interconnected with the growth of alternative data, the inflexibility and poor traditional frameworks become much starker. This signals the need for more flexible, robust, and adaptive frameworks for portfolio construction and optimization.

Machine Learning Approaches for Portfolio Optimization:

Supervised Learning for Return Prediction and Portfolio Construction

Lately, the importance of supervised learning models in financial forecasting has expanded, particularly in the context of optimizing portfolios. This was justified by considering the algorithms' adeptness at handling stochastic and dynamic shifts in the market compared to more classical methods.

Nonetheless, these models have been deployed to more complex tasks than just simple return forecasting, and these tasks include building full-fledged portfolios. In the literature, novel integrated methods have been constructed that combine optimization techniques and predictive models for this purpose. Huang, Dang and Bhuiyan (2025) developed a new Mean-Variance-Forecast-Error (MVF) model that integrates prediction uncertainty into the optimization objective function. In traditional methods, ignoring forecast biases when allocating weights can be problematic. This approach improves the connection between trustworthiness of a prediction and the construction of a portfolio.

Deep Learning and Temporal Pattern Recognition

Deep learning approaches, particularly LSTMs, have used for a long time for capturing temporal dependencies in market data, notably in financial problems involving time series. LSTMs have excelled in forecasting financial time series than traditional recurrent neural networks because LSTMs solve the gradient vanishing problem with their gating mechanism, allowing for the capturing of long-term features (Wang et al., 2024).

Of great importance, the architecture for deep learning in (for) portfolio management continues extending the complexity. Recent literature has been studying the fusion of pattern recognition CNNs with sequential modeling LSTMs and attention neural networks for time focusing in financial data. These complex architectures outperform single models in imitating certain market behaviors. The complex architectures, however, do require more data for training. These varying effects hinge particularly on market conditions emphasize the relative importance in the choice of the model to the specific investment strategy and the attributes of the data for the intended analysis. This is the case for a large share of complex architectures for deep learning in portfolio management.

Reinforcement Learning for Adaptive Portfolio Management

Reinforcement Learning (RL) is shaking up the world of portfolio optimization by creating a direct link between market conditions and investment allocations, all in the name of maximizing returns over time. This method is particularly adept at tackling dynamic challenges, such as transaction costs and multi-period optimization, which traditional approaches often overlook by referring to fixed correlations. Recent advances, like the gymfolio framework and stacked ensemble strategies, have demonstrated remarkable success, with one model even outperforming the best individual strategy by

15%. However, despite its strengths in adapting to ever-changing market conditions, RL still grapples with some tough hurdles, including sample efficiency, reward engineering,and the potential for overfitting to past data, all of which needs to be navigated with care.

Table 2.1: Summary of Machine Learning Approaches in Portfolio Optimization

Approach	Key strengths	Common Algorithms	Notable Applications
Supervised Learning	Effective return prediction	-Random Forest	-Return forecasting
	-handles non-linear relationships	-XGBoost	-Feature importance analysis
Deep Learning	-Captures temporal dependencies	-LSTM	-Time-series forecasting
	-models complex patterns	-CNN	-Pattern recognition in market data
		-Hybrid models	
Reinforcement Learning	-Adaptive policies	-DDPG	-Dynamic portfolio allocation
	-multi-period optimization	-Q-learning	-direct weight optimization
	-handles constraints	-Policy gradients	

Comparative Performance and Emerging Trends

Machine learning techniques not only exceed classic methods of portfolio optimization, but they also exceed them in various markets and asset classes. One example using South African equities found that portfolios utilizing machine learning methodologies not only attained a higher Sharpe ratio, but also managed risk better and forecasted tail risk events more accurately. This uneven advantage during times of stress in the financial market is substantial, because machine learning algorithms can dynamically and quickly shift portfolio weights during turbulent times, something many of the static models simply cannot do.

The application of ML in portfolio construction goes beyond the use of machine learning models towards the development of integrated hybrid frameworks consisting of ensemble methods. In this context, no single algorithm performs best under all market conditions. One example of this is in the research direction of combining predictive models with optimization frameworks which include controls for predicting uncertainty. Another example of a risk mitigating technique is ML-based hierarchical risk parity models which automatically group securities based on risk features and not correlations, shifting the model away from dependency on weak correlations for achieving risk-based diversification.

The challenges of ML automatic portfolio optimization remain considerable. One major hurdle is model interpretability. In the case of complex neural networks, they can serve as a black box where the rationale for a portfolio construction can become hidden. Also, the reliance on the quality of the data and the overfitting of data to the historical patterns of the data necessitate the development of strong validation frameworks. Researchers argue that the effectiveness of various ML techniques is dependent on the specific market regime, asset class, and investment horizon, thereby underscoring the importance of context-sensitive model selection.

Conclusion and Research Gap

There is clear evidence of a shift from static classic portfolio optimization methodologies to predictive supervised learning, and now, adaptive policy-based reinforcement learning frameworks. Such change attempts to overcome the primary shortcomings of the conventional portfolio optimization methods, specifically, the lack of consideration for the financial market intricacies, including their dynamic, non-linear, and non-stationary properties. In empirical studies, ML methods outperform traditional approaches, especially in their ability to pattern recognize, mitigate risk, and adjust to fluctuations in market conditions.

Despite the progress made, the literature still has significant research gaps. Although individual ML models have been well-researched and documented, a direct comparative study of various ML model families within a cohesive analytical framework is still lacking. Much of the literature tends to emphasize the value of a solitary approach, or comparative studies primarily focus on a recently proposed technique with limited benchmarks, thus providing little guidance on the comparative advantages and disadvantages of different ML approaches for portfolio optimization. This is especially concerning given the differences in the computational intensity, data requirements, and overall complexity of the practical application of each of the ML methods.

This study aims to fill this research gap by providing a systematic empirical analysis of four widely referenced ML algorithms for portfolio optimization. Specific contexts in which each methodology excels will be revealed through iterative development, backtesting, and evaluation. Practical guidance will be extended to portfolio managers and financial engineers interested in implementing ML methodologies, while academic knowledge will be enriched on the ways different algorithms encapsulate market phenomena, and on robust portfolio construction.

Competitor Analysis

Abstract

For decades, Modern Portfolio Theory has shaped how investors think about diversification and risk. Yet, the cracks in that framework become clear during turbulent markets. Returns are rarely normal, correlations spike unexpectedly, and the models stumble. In recent years, machine learning and deep learning have provided more flexible ways to build portfolios. This paper looks at how a hybrid system—using long short-term memory networks, gradient boosting, and reinforcement learning—compares with existing approaches in both academia and industry. Through competitor analysis and SWOT evaluation, I argue that the project offers something different: a balance of resilience, transparency, and market practicality.

Introduction

When Harry Markowitz published Modern Portfolio Theory in 1952, he gave finance its first real quantitative framework. Students still learn it today. But anyone who has lived through a financial crisis knows the pitfalls. Correlations don't stay stable, distributions aren't normal, and markets certainly don't behave rationally (Merton 1972; Taleb 2007).

That is why finance has increasingly borrowed from computer science. Machine learning and deep learning methods don't assume tidy equations. Instead, they pick up on hidden patterns and adapt when things shift. The project examined here pulls several tools together: LSTMs to catch time-series dynamics, XGBoost for sharper return forecasts, and reinforcement learning to keep allocations responsive to new data.

The aim is not simply to "beat the benchmark." The bigger ambition is to design a strategy that can handle stress—something that stays standing when conditions get messy. To see how original that is, we need to compare it with what academics, robo-advisors, hedge funds, and open-source communities have already built.

Literature and Industry Review

In theory, MPT was groundbreaking (Markowitz 1952). In practice, it is fragile. Small mistakes in estimating inputs can throw off allocations completely, and during market turmoil the assumptions collapse (Merton 1972).

The Black–Litterman model (1992) softened some of those weaknesses by mixing investor views into the optimization. The portfolios looked smoother, but the framework still leaned on equilibrium and linearity, which don't always exist in reality.

Machine learning added new energy. Random forests (Breiman 2001) and XGBoost (Chen and Guestrin 2016) improved prediction accuracy, though at the expense of interpretability. They tend to act like black boxes.

Deep learning moved the conversation forward in a way traditional models couldn't. Long short-term memory networks (Hochreiter and Schmidhuber 1997) shine when the problem involves recognizing sequences—exactly the kind of temporal dependencies we see in returns. Reinforcement learning, first adapted to trading by Moody and Saffell (2001), works differently: it learns by trial and error, adjusting its choices much like a trader learning from the tape. That similarity to human intuition makes it attractive, but it comes with baggage. These models need vast amounts of data and can wobble badly if not tuned with care, which makes them as fragile as they are impressive. These methods are powerful, but they are not free of issues: they require lots of data and can become unstable if tuning is off.

On the industry side, robo-advisors like Betterment and Wealthfront scaled quickly by offering automated portfolios at low cost. Their strategies, however, are still rooted in mean–variance optimization with only modest tweaks (Lam 2016).

At the opposite end, quant hedge funds such as Renaissance Technologies and Two Sigma use sophisticated ML pipelines and alternative data. They often succeed, but the details are proprietary, which means outsiders benefit little from their innovations (Lo 2017).

Finally, the open-source ecosystem has started experimenting with RL-based trading frameworks like TensorTrade and FinRL. They're useful as sandboxes—you can test ideas quickly and see what sticks. But once you move from a notebook to real markets, most of them show their limits. Stress testing, liquidity checks, and other hard realities are usually missing, which is why these projects often stumble outside the lab.

What emerges is a split: accessible but oversimplified solutions for retail investors, and highly advanced but closed systems for institutions. There's little available in between.

SWOT Analysis of Competitors

Modern Portfolio Theory has the advantage of simplicity and a strong academic legacy. It is easy to teach and apply, but its flaws are glaring: fragile inputs and poor performance when markets turn volatile.

Robo-advisors, meanwhile, have grown popular by making investing easy and cheap. Anyone with a phone and a few hundred dollars can get a portfolio built for them in minutes. That convenience explains their success. But the trade-off is that they rarely go beyond cookie-cutter questionnaires and static optimization models. As ETFs keep evolving and fees shrink further, there's a real chance these platforms start looking interchangeable, almost like utilities rather than differentiated services.

Quant hedge funds like Renaissance have shown what is possible with advanced ML. Their strength is obvious: resources, data, and technical talent. The weakness is just as clear: opacity. They benefit their investors, but contribute little to broader knowledge.

Open-source platforms demonstrate creativity. They lower barriers for experimentation and inspire students and researchers. Unfortunately, they often lack the robustness needed for live trading. Most open-source efforts skip important safeguards—liquidity checks, stress tests, and simulations of rare but catastrophic events. That gap matters because in real markets, those are often the breaking points. The hybrid project tries to close that hole. By weaving LSTMs, XGBoost, and reinforcement learning into one framework and pairing them with explicit robustness checks, it positions itself as something sturdier. The design avoids the traps of being too simple to matter or too fragile to trust. The trade-off, of course, is complexity and computational cost.

Unique Findings and Market Gap

Four insights came out of the competitive analysis.

- Traditional models are fine for the classroom, but when markets seize up, they crumble—hardly the kind of reliability investors need.

- Robo-advisors do meet the hunger for automation, and they've proven people want data-driven tools, but they're shallow and leave plenty of room for someone more advanced to step in.

- Hedge funds, for their part, remain the real labs of innovation, but their secrecy means the knowledge rarely spreads.

- Open-source projects, while fast-moving and creative, often ignore the gritty details like robustness and liquidity that matter most in the real world.

This project addresses those gaps head-on. It blends different ML methods rather than relying on just one. It makes robustness a central design principle—through liquidity-adjusted allocations, crisis scenario testing, and Monte Carlo tail analysis. And it does so transparently, unlike hedge funds. The choice to stick with highly liquid assets may sound obvious, but it's crucial. It means the strategy isn't just a neat idea for a paper or a backtest—it's something that could actually be executed in real markets without running into slippage or liquidity traps.

In short, the project contributes both to research—by offering a replicable hybrid framework—and to practice, by giving fintech firms and sophisticated retail investors a tool that is adaptive yet accessible.

Comparative Analysis

Line the competitors up side by side, and the differences come into focus. Traditional finance is elegant but brittle. Robo-advisors scale but remain shallow. Hedge funds innovate but keep their work hidden. Open-source projects bring a lot of creativity and transparency to the table, and that makes them exciting to watch. The problem is that once you put them under the weight of actual market conditions, most can't quite keep their footing.

What sets the hybrid project apart is that it doesn't lock itself into one camp. It borrows adaptability from hedge fund models, takes a measure of transparency from open-source platforms, and still holds on to the academic rigor that makes it credible. That mix is unusual, and it helps the project sidestep many of the weaknesses that drag down its peers. By stress-testing across multiple regimes and factoring in liquidity, it goes further than most competitors in proving robustness.

Business Case and Market Viability

From a commercial standpoint, the timing could hardly be better. Investors these days aren't just chasing performance; they also want to understand the tools managing their money, and regulators are asking the same questions. Meanwhile, fintech firms find themselves jostling in a crowded robo-advisory market. With so many players offering similar services, it's becoming harder for any one platform to distinguish itself from the rest.

This project manages to answer both sides of the problem. On one hand, it has academic credibility because the methods are laid out openly and can be replicated. On the other, it's grounded in practice—it works with liquid assets and can stretch across different markets. The real value lies in how it balances accuracy with resilience. That combination gives fintech firms a way to stand out in a crowded field and gives institutions something they can defend when questions come up in a risk committee.

Conclusion

Portfolio allocation may be an old problem, but many of today's solutions remain incomplete. Traditional methods are too brittle, robo-advisors too shallow, hedge funds too closed, and open-source projects too fragile. The hybrid approach discussed here takes a different path. By combining LSTMs, XGBoost, and reinforcement learning, and by embedding robustness at every stage, it delivers a system that is both innovative and usable. That dual contribution—novel in research and practical in markets—is what makes it significant. In a world where shocks are inevitable, building resilience into portfolio design is not optional; it is essential.

Source Code Repository

You can find a link below to the online repository that holds the source code, dependencies, and (for now) the initial findings for this project. The repository is designed for easy viewing and replication of the results.

Repository Link: https://github.com/Davide-666/WQU-MScFE-Capstone

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